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ABSTRACT

A cognitively based theoretical framework for the assessment of domain competence is proposed. The basic thesis is that to be knowledgeable one must know how the important concepts of a domain are interrelated. This thesis implies that any valid assessment of knowledge must capture these structural properties. The implementation of a structural approach in the assessment of classroom learning is described, and recent findings with college students demonstrating the ability of the approach to predict classroom examination performance are reviewed. The success of the approach is discussed in terms of the benefits derived from integrating the cognitive emphasis on structure and the psychometric emphasis on predictiveness. Thirty-three references and two figures are included. (Author/SLD)

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# STRUCTURAL ASSESSMENT OF KNOWLEDGE AND SKILL



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A cognitively-based theoretical framework for the assessment of domain competence is proposed. The basic thesis is that to be knowledgeable one must know how the important concepts of a domain are interrelated. This implies that any valid assessment of knowledge must capture these structural properties. We describe the implementation of a structural approach in the assessment of classroom learning and review recent findings demonstrating its ability to predict classroom exam performance. The success of this approach is discussed in terms of the benefits derived from integrating the cognitive emphasis on structure and the psychometric emphasis on predictiveness.

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A Structural Cognitive Approach to the Assessment of Classroom Learning

The present paper describes a method of assessing classroom knowledge that involves an integration of psychometric and cognitive perspectives. Perhaps because of their different interests these two approaches historically have had relatively little influence on one another. Whereas psychometricians are primarily concerned with the predictiveness of a measure, cognitivists have been more concerned with representational models of knowledge. In this paper we hope to show that there exists a natural synergism between the cognitive and psychometric approaches that when appropriately integrated can mutually facilitate progress towards their respective goals. More specifically, the cognitive perspective, with its structural assumptions regarding the representation of knowledge, can provide the basis for some new and useful methods to assess classroom learning. The psychometric approach, on the other hand, with its emphasis on test validity and reliability, can provide a much needed empirical basis for models of knowledge representation.

We begin this paper by contrasting the cognitive approach and the psychometric approach as they are implemented in classroom assessment. We then turn to a more detailed discussion of a structural approach to knowledge assessment, which integrates the cognitive and psychometric perspectives within the context of classroom learning.

Two Contrasting Perspectives on Knowledge Assessment

The psychometric approach, as applied in the classroom setting, usually assesses knowledge with conventional essay, true-false, and multiple choice exams. A student's performance on this type of exam is usually represented in terms of a percentage correct. Many educators are perhaps so familiar with this generic form of examination in their classes that they no longer consider the assumptions underlying this "how much" approach to knowledge assessment. By accumulating points across questions, we are assuming a kind of independence that suggests we conceptualize knowledge as a list of independent facts or elements. Although this criticism maybe less true of essay exams, it remains the case that using a single index, such as percentage correct tells us very little regarding what a student knows or does not know.

An simple list of item may serve as an appropriate representation for certain limited domains (e.g., the capital cities for the 50 states of this country), but there is a great deal of empirical and theoretical work from the cognitive literature, suggesting that a list is not a valid means of representing more complex domains of knowledge (e.g., Chi, Glaser, & Farr, 1988; Genter & Collins, 1983). A commonly held and long-standing assumption in cognitive psychology is that knowledge is organized and structured (Bower, 1975; Tulving & Donaldson, 1972; Wertheimer, 1945). From the cognitive perspective, to be knowledgeable of a domain, one must understand the interrelationships among the important concepts within the domain. Consistent with this assumption, cognitive models of knowledge representation are

primarily concerned with the types of structures that organize bodies of knowledge. In fact, the meaning of any specific concept is assumed to be largely dependent on its interrelationships with other concepts. Although there are a variety of structural models of knowledge in the cognitive literature (e.g., Anderson & Bower, 1973; Collins & Quillian, 1969), most share a central theme in assuming that the interrelations among concepts is an essential property of knowledge.

As Shavelson and colleagues (Schavelson, 1972; Schavelson & Stanton, 1975) realized some two decades ago, this assumption regarding the representation of knowledge has some important implications for the assessment of classroom learning. Basically, how we assess knowledge should be consistent with how we assume knowledge is represented. If structural properties are an important component of knowledge representation, then our assessment tools must measure these structural properties. Over the past few decades, an impressive literature has accumulated indicating that the structural properties of domain knowledge are closely related to competence in the domain (e.g., Chase & Simon, 1973; Chi, Glaser & Rees, 1981). From this perspective, knowledge of a domain implies at some level understanding how the various domain concepts are interrelated. This view strongly suggests that our methods of assessment must capture this structural component of knowledge in order to be valid.

An obvious implication is that we should use some type of cognitive representational model to assess an individual's knowledge of a domain. In the next section we describe in some detail how a structurally oriented approach to knowledge assessment can be successfully implemented. However, before we conclude this section we need to discuss how the structural assessment approach is mutually beneficial to the cognitive approach and the psychometric approach as it is applied in the classroom. Its potential benefits to the psychometric approach are twofold. First, it would more solidly ground classroom evaluation in a context of knowledge representation theory. Secondly, if structural aspects of knowledge are related to domain performance, the assessment of these structural properties should improve prediction. Finally, as will be discussed in some detail later, the representation may be presented in the form of a visual graph that allows the instructor to more easily identify the locus of a student's misconceptions regarding the domain. This in turn could facilitate individualized training intervention.

One benefit of a structural approach to assessment for cognitive theory is that it provides an empirical basis for evaluating different representational models of knowledge. This type of representational validation has been largely lacking in the cognitive literature. As will become apparent when we describe the implementation of the structural approach, the structural representations are evaluated in terms of their ability to predict classroom exam performance. In other words, each student will have her unique, empirically derived representation of a knowledge domain. Thus, predictive validity plays a central role choosing a theoretical representation of domain knowledge. This stands in contrast to the methods by which most cognitive represesntational models are validated. Cognitivists have been far more concerned with issues relating to the architecture of their

models of semantic memory and knowledge representation. Among other things, these models attempt to capture the way we rapidly access and retrieve various bits of information from memory. Experiments designed to test these models often look at how stimulus parameters (e.g., word length) influence response latencies. The models are intended to apply to large populations (e.g., native English speaking adults), or specific groups (e.g., expert programmers), with little or no interest in individual differences.

In summary, our aim is to build some bridges between applied educational testing and cognitive theories of knowledge representation. We believe the schism between the two fields is unnecessary and counterproductive. It developed, we believe, primarily out of their different interests. The cognitivists were concerned with the development of models of cognitive representational systems, whereas the educational assessment researchers were more concerned with the immediate issues of validity and reliability. Indeed, there exists a natural synergism between the two fields that could be mutually beneficial to the progress of both. Specifically, we hope to show that test theorists' concerns with predictiveness will benefit modeling of cognitive structure, and the cognitivists' structural perspective will positively influence the development of the methods used to assess domain knowledge.

## Structural Assessment: Methods and Findings

In this section we provide a general methodological overview of structural approaches to knowledge assessment, with special emphasis on methods we have developed over the past few years. Although not a comprehensive review of the literature, the discussion should give the reader a basic understanding of the structural approach, how it differs from more conventional testing approaches, a smattering of relevant findings, and some of the more important issues and implications viewed from the structural perspective.

Research on structural knowledge assessment in classrooms began to appear, primarily in educational psychology journals, in the late 1960's and early 1970's (e.g., Johnson, 1967; 1969; Kass, 1971; Shavelson, 1972; Shavelson & Stanton, 1975). Several investigators reported encouraging findings, indicating that classroom performance was related to students' structural organization of the central concepts in the course. For example, Fenker (1975) had students in a measurement class and a design class rate the relatedness of pairs of concepts and then transformed their ratings to an MDS spatial representation. The students' MDS representations were then compared with a referent representation based on the average ratings of eight experts in each domain. He found that students' similarity to the referent structure was correlated ($r=.54$) with course grades in the design course, and ($r=.61$) with grades in the measurement course. Despite the generally positive outcome of this early work, there were a number of specific methodological problems that hampered further advances. Perhaps foremost was the lack of quantitative methods for evaluating structural representations. We believe that our current research has made significant progress in addressing these issues.

Our discussion of structural assessment methods is organized in terms of the three major steps that are involved in their implementation: (a) elicitation - evoking some behavioral index of an individual's organization of domain concepts; (b) representation - applying techniques that transform the elicited data into a representation that captures the important structural properties of domain knowledge; and (c) evaluation - quantifying the level of knowledge or sophistication that is reflected in the representation.

Elicitation

Elicitation, as the word suggests, is the process of evoking or extracting what a person knows about some knowledge domain. There are a wide range of methods for eliciting knowledge, ranging from direct approaches, such as interviews and conventional essay exams, to more indirect approaches where, for example, knowledge may be inferred on the basis of reaction times (e.g., Collins & Quillian, 1969).

One important point about elicitation is that the method of elicitation should be compatible with the cognitive model of knowledge representation. Thus, if it is assumed that knowledge is structural in its representation, it follows that the elicited behavior should be sensitive to the interrelationships among the concepts. The implications of this assertion will be better appreciated after we have discussed the elicitation, representation, and evaluation phases of the structural approach. For the present, it suffices to say that the elicitation procedure must provide some indication of the relatedness between pairs of concepts. With an appropriate representational transformation of these relatedness ratings it should be possible to capture more global structural properties of domain knowledge.

Although a variety of elicitation methods have been used to obtain concept relationships, including word associations (Johnson, 1967), ordered recall (Cooke, Durso, & Schvaneveldt, 1986), and card sorting (Shavelson & Stanton, 1975), simply having subjects make subjective ratings of degree of relatedness between pairs of concepts works quite well in assessing an individual's knowledge of the interrelations among domain concepts (Fenker, 1975; Goldsmith, Johnson, & Acton, 1991). Furthermore, there may be certain advantages to using relatedness ratings to elicit domain knowledge. First, subjects have no difficulty using a numerical scale to express their sense of relatedness. As a result, it is relatively simple to automate the administration and scoring of the ratings. This allows for the objective and efficient gathering of large amounts of relatedness data. Second, unlike essay exams and interviews, relatedness ratings do not assume that subjects have conscious access to all relevant knowledge. In fact, in our own work we have found that requiring subjects to make rapid relatedness judgments on the basis of their initial intuitions may result in more reliable and valid ratings than allowing unlimited time.

Two questions about concept selection inevitably arise when using relatedness judgments to assess domain knowledge, namely, how many and which concepts should be rated? Not surprisingly, these two questions are closely related, since the number of concepts required to obtain a valid assessment is likely to depend on how the concepts are selected.

In deciding on the number of concepts to be rated we must consider how

the number of concepts influences the total number of pairs that are rated. At the extremes each concept could be paired with one or all other concepts in the list. Because some structural methods of analyzing ratings require that data be collected on all pairwise combinations of concepts (e.g., Pathfinder, Schvaneveldt, 1990), we will focus the discussion on this case. When all pairwise combinations of concepts are rated for _n_ concepts, there will be [n(n - 1)/2] pairwise ratings. For example, 24 concepts would result in 276 pairs, which requires approximately 45 minutes for most students to complete. For practical considerations, including attention span and fatigue, this sets an upper limit of approximately 30 concepts we can expect students to rate in a single session.

In one study (Goldsmith, Johnson, & Acton, 1991) involving an undergraduate course in design of experiments, we found that when students rated all pairwise combinations of concepts, predictiveness of course performance improved in a linear manner from .15 to .74 as the number of concepts rated increased from 5 to 30. Although this suggests that more is better, we have found with 24 concepts predictions of college classroom course performance ranged from approximately .50 to .85 across several different domains (cognitive psychology, computer programing, and design of experiments).

We turn next to the question of how concepts are selected. We first attempted to generate a fairly comprehensive list of the important concepts in a subject by analyzing the glossary and index of relevant textbooks. We then conferred with the course instructor, to add any important concepts that were missing. From this list we selected a sample of concepts (usually 24) that the instructor agreed were representative of the course material.

Considerable work is left to be done on developing a set of criteria to serve as a systematic basis for selecting concepts. One obvious criterion proposed by Hirsch (1987) and Boneau (1990) is the concept's importance to the domain, as judged by experts. Being knowledgeable of the most important concepts within a domain may be sufficient if our only goal is to define some basic level of competence, but these concepts may not adequately discriminate among higher levels of expertise. Thus, another basis for selection would be to select those concepts which best discriminate between levels of expertise.

Selecting concepts on the basis of their correlation with exam scores is similar to the item selection procedure commonly used in test construction (Anastasi, 1988). When this procedure is used in test development it applies to specific items, whereas in the rating task the selection of a concept would imply that it would be paired with the other _n_-1 concepts. Thus, item selection may be more efficiently applied to pairs of concepts than individual concepts.

Recently, we have found (Goldsmith & Johnson, 1990) that by selecting the more predictive pairs, it is possible to predict classroom exam performance as well with ratings of 100 or fewer selected pairs, as with all 276 pairwise combinations of 24 concepts. Simply in terms of prediction there appear to be obvious benefits to employing an item selection procedure. However, there is a cost when it comes to transforming the ratings into a

structural representation. This will become more apparent in the next section, where we discuss the representation of the elicited knowledge.

Representation

Once we have elicited an individual's concept interrelationships in a domain, we must decide how to transform these raw proximities into a representation that best models the individual's knowledge. We mention three important criteria in choosing a representation. First, the representation should have acceptable predictive validity. That is, we should be able to predict an individual's level of competence in a domain at least as well with the representation as with the untransformed ratings.

Second, the representation should be easily comprehended. One advantage of many scaling algorithms is that they result in visual representations depicting the organization among concepts in a manner that is relatively easily interpreted. For example, cluster analysis represents the concepts organized in terms of a hierarchical graph (Johnson, 1967; Milligan & Cooper, 1987). Thus one can see by visual examination how an individual organizes the concepts within a domain.

Finally, the representation should be consistent with our theoretical conceptions of knowledge. In the case of conventional exams we often simply use the percentage correct to represent what an individual knows about some domain. As argued above, this method suggests that knowledge can be conceptualized as an accumulation of independent facts. A percentage index estimates the proportion of information known. Although the information may actually involve understanding certain conceptual relationships, a percentage does not explicitly reflect the structural properties of the individual's knowledge.

The next question is to determine which type of representation better models the specific structural property that is assumed to be important. There are a variety of scaling procedures that researchers have historically used to infer the structural organization underlying similarity judgments. One of the more frequently used methods is multidimensional scaling (MDS) (e.g., Kruskal, 1964), which represents a set of concepts in terms of an *n*-dimensional Euclidean space. Other scaling algorithms such as cluster analysis (e.g., Johnson 1967) and additive trees (Sattath & Tversky, 1977) result in hierarchical graph representations. A more recently developed scaling algorithm, Pathfinder (Schvaneveldt, 1990) also organizes the concepts into a connected graph representation, but Pathfinder does not impose a hierarchical solution and thereby allows greater freedom in developing an individual's structural graph.

To provide a concrete illustration of a Pathfinder network, Figures 1 and 2 show Pathfinder solutions for an expert's and a novice's ratings of 24 concepts from a cognition and memory course. Those readers having some background in cognitive psychology will see that, while some of the novice's structure is quite reasonable, it reveals a number of either missing or inappropriate relationships.

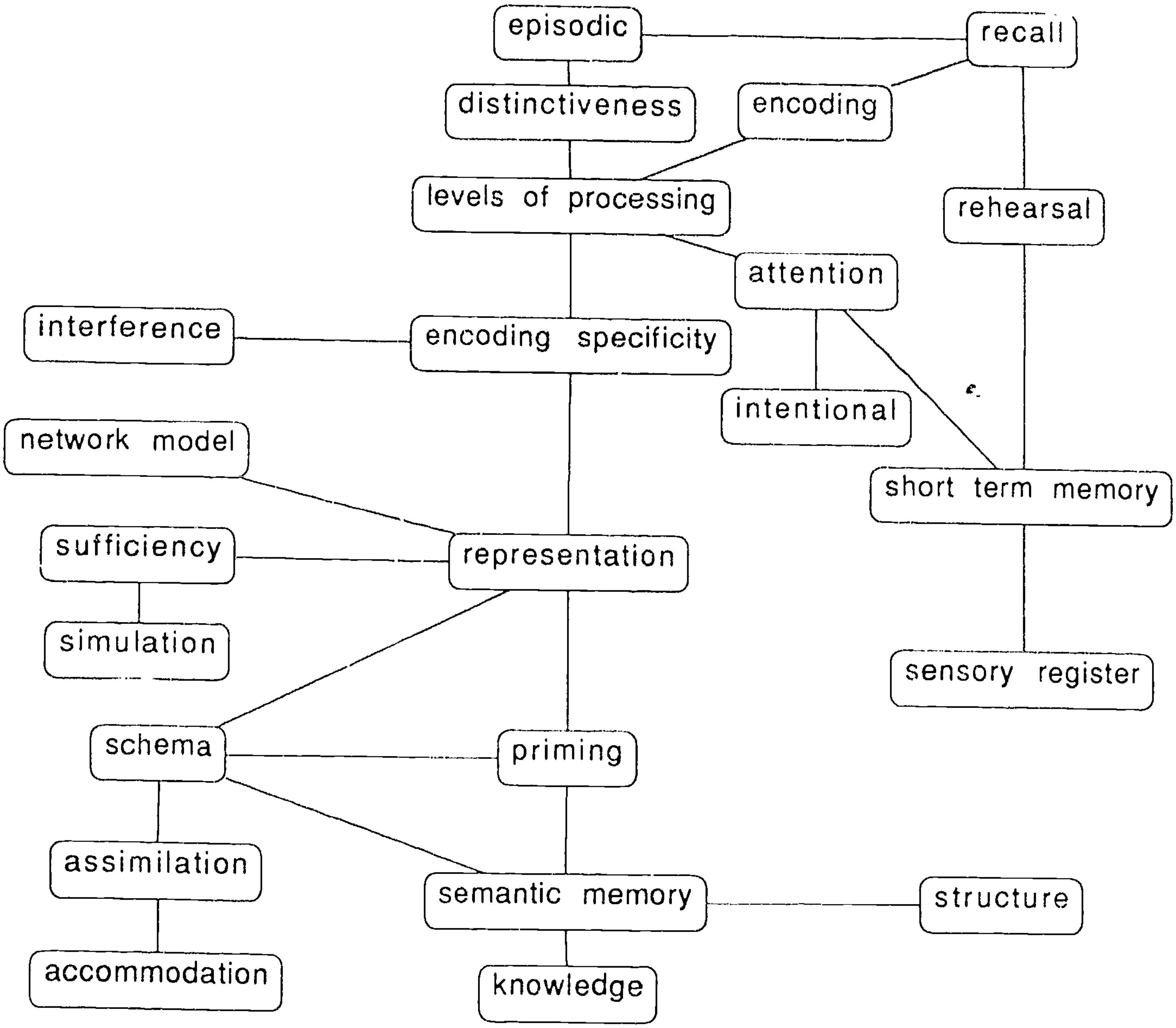


Figure 1 Pathfinder network solution to expert's ratings of 24 concepts from course on cognition and memory.

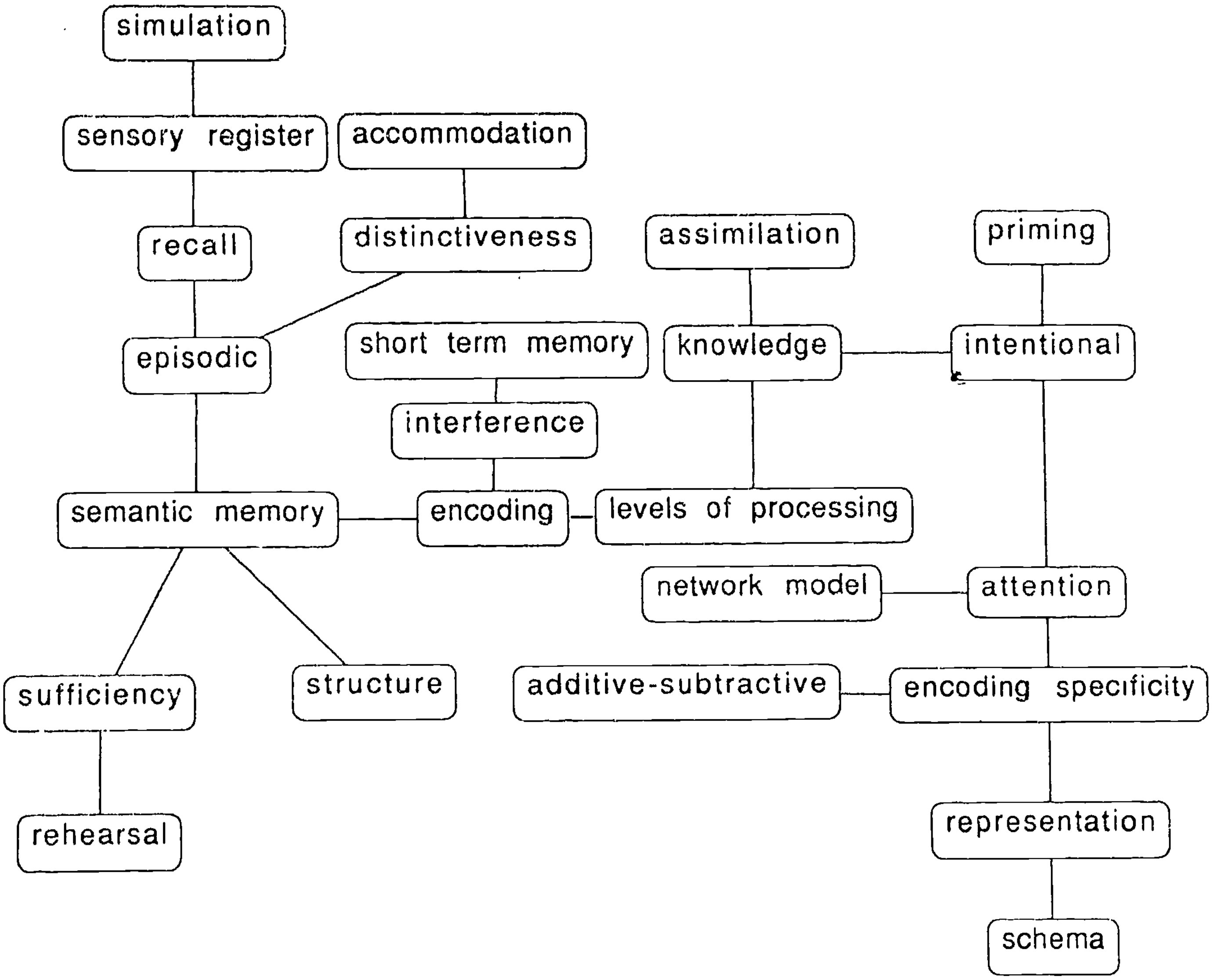


Figure 2. Pathfinder network solution to undergraduate student's ratings of 24 concepts at end of semester.

In choosing a type of representation, all of the above criteria must be considered. If the research is theoretically motivated the theory will suggest the structural properties that are of primary interest, and this will likely favor one representational approach over others. For example, there is evidence (Holman, 1972; Pruzansky, Tversky, & Carroll, 1982) suggesting that spatial representations, such as MDS, work better for perceptual phenomenon (e.g., color represented in terms of a three dimensional space involving hue, saturation, and brightness), whereas network representations are better for conceptual phenomena (e.g., a biological taxonomy of animal species).

If, on the other hand, the research has a more applied orientation then ease of representation may play a more important role. For example, assume the goal is to design an individualized curriculum that is aimed at addressing specific knowledge deficits within a domain. This process could be facilitated with the use of network representations, such as those presented in Figure 1. By visually examining student and expert networks, it could be determined which specific clusters or connections were missing from an individual student's organization of a domain.

Finally, the choice of representation can be based on predictiveness. Using this criterion, the type of representation that provides the best prediction of domain competence is preferred. We believe that the predictiveness criterion, if used in moderation, could have a healthy influence on the theoretical development of cognitive representations by forcing the representations to make more fine-grained distinctions. Many models of knowledge representation (e.g., Collins & Quillian, 1969) are able to make very general predictions regarding the organization of knowledge (e.g., the attribute of singing is more closely related to canaries than is the attribute of eating), but they fail to address individual differences in domain competence.

There is a danger of overemphasizing predictability as a basis for favoring a particular representational transformation. On first consideration it may appear that predictability is a completely objective basis of evaluating the validity of alternative representations. This assumption, however, is only true to the extent that the external criterion that is being predicted is an objective definition of competence. In the case of our own work we have been using course points from classroom exams as the external criterion. At some point we must ask ourselves if we would be happy if our structural measure correlated perfectly with exam scores. Obviously not. The point is, we doubt the ultimate validity of conventional exams, but we must use them as a means of bootstrapping a new alternative. The eventual acceptance of a structural approach to assessment will rest upon a multitude of criteria. Thus, the overemphasis on a single criterion at this early juncture is likely to be misguided.

In concluding our discussion of knowledge representations, it should be apparent that research and theory in this field is still in its infancy. It is far too early to exclude alternative representational systems from further consideration on the basis of the preliminary data that is currently available. We are proposing a broad scale program of research in which

different investigators will explore a variety of methods and applications. The problems are sufficiently complex to accommodate more than a single model.

Evaluation

The third step in knowledge assessment is to evaluate an individual's knowledge representation. What level of sophistication or competence is indicated by a particular representation? Clearly, we must have some means of transforming a representation into a simple index of competence. We will discuss two fundamentally different methods of evaluation. One approach we call referent-based, in which the student's representation is compared against some external standard. In referent-based evaluation some index of similarity between the student and expert referent representation is used to predict domain competence (e.g., classroom exam performance). The other approach to evaluation is referent free in that the assessment refers to intrinsic properties of the student representation.

Referent Based Evaluations. When attempting to assess domain competence, the most obvious external standard is an expert or group of experts in the field (Chi, Feltovich, & Glaser, 1981). In our work, when assessing college classroom knowledge, course instructors naturally serve as experts. Often we have averaged the instructor's ratings with a number of other faculty and graduate students who have taught similar courses. We find that a referent structure based on the averaged ratings of a number of experts is usually a better predictor of exam scores than one based only on the ratings of the individual instructor for the course (Acton, 1990). This finding has some important implications. Specifically, it allows for the possibility of moving towards an idealized referent structure that transcends the various idiosyncrasies of individual experts. We must emphasize that the idea of an idealized referent structure does not in any way constrain individual creativity. The fact is, although expert structures are more similar to one another than novice structures, each expert's organization has unique characteristics.

Precisely how the comparison between student and expert representation is carried out depends, in part, on the type of representation being compared. To begin, we can take the relatedness ratings matrix itself as a raw representation of an individual's knowledge. The most obvious and direct way to assess the similarity between two proximity matrices is simply to compute the correlation between the two sets of ratings. We have found this measure of similarity to be a good predictor of classroom exam performance with correlations between similarity and total points on exams ranging from .45 to .83 across different semesters and different courses.

Although the correlations on raw ratings may perform quite well as a predictor, it does not fare well on the other two criteria by which we evaluate representations. First, a matrix of ratings is not easily comprehended, and second, it is not motivated from any explicit theoretical perspective. If we adopt a structural approach, we want to look at representations and methods of comparing representations that emphasize structural properties. Recall that our definition of structure focused on the interrelationships among concepts, which we believe is best captured by network representations. We also hypothesized that the meaning of an

individual concept is defined in terms of the concepts that are closely related to it. This has some important implications for how we evaluate the similarity between two networks.

When evaluating Pathfinder derived network representations, it is quite possible to quantify the similarity between a student and expert network graph by simply correlating the graph distances between respective pairs of concepts. However, this correlational measure of similarity does not capture the more global properties of our definition of structure (viz., a concept which is defined by its neighbors). To overcome this limitation, we developed (Goldsmith & Davenport, 1990) a set theoretic measure called C that reflects the similarity in neighborhoods between two concepts. For example, assume that concept A in a student's network is directly linked to concepts B, C, and D, whereas concept A in the expert's network is linked to concepts B and C. The measure C is the ratio of the size of the intersection (B and C) over the size of the union (B, C, and D) or .67. We do this for each concept and then simply average the ratios over all the concepts. We have found the similarity measure C of Pathfinder networks to be a better predictor of exam scores than correlational measures on raw proximity data, network distances, or Euclidean distances derived from MDS scaling (Goldsmith, Johnson, & Acton, 1991).

The point is not that using C on Pathfinder networks was necessarily a better predictor, but that our methods of assessment are consistent with our view of domain knowledge. It is quite possible that other measures and other domains may yield different outcomes. Although we expect that methods emphasizing structural properties of knowledge will generally do a better job of assessing domain knowledge, the important point is for researchers and practioners to adopt a coherent and theoretically principled approach to assessment.

Referent Free Assessment. Most methods for evaluating domain knowledge involve an external criterion or referent. For example, in conventional testing there is the externally defined "correct answer" against which performance is evaluated. In contrast, we might look for intrinsic properties of behavior that are indicative of expertise. Once again, the specific intrinsic properties we look for should be consistent with our theoretical conceptions of domain knowledge.

In our structural approach to knowledge assessment we have assumed that a concept's meaning is contained in its relationships to other concepts (i.e., its neighbors) within the domain. Therefore, if concepts A and B are neighbors, and concepts B and C are neighbors, there is an increased likelihood that concepts A and C are also neighbors. As an individual becomes more knowledgeable we would expect her judgments of relatedness to become more constrained by these neighborhood factors. How might one go about quantifying this type of constraint? Our approach is to first, use the C measure described above to compute a derived distance between all pairs of concepts on the basis of neighborhood similarity. Next, we compute the correlation between the raw ratings and the derived ratings for all pairs of concepts. We call this measure coherence. We have found coherence to be a reliable predictor of student's classroom knowledge. In addition, coherence increases across levels of expertise ranging from naive student to knowledgeable

undergraduate to graduate student to professor (Acton, 1990).

Another type of referent free property of relatedness ratings is the consistency with which repeated pairs of concepts are rated. In our rating task we usually repeat approximately 10% of the pairs, and then compute the correlation between repeated ratings for each individual. We find that this index of reliability is significantly correlated with exam performance. Not surprisingly, it is easier to be consistent when you are knowledgeable of the concepts you are rating.

To summarize, we have proposed two methods of evaluation, referent based and referent free. In the case of referent based evaluation we noted the advantages of using expert referent representations based on the averaged ratings of several experts and alternative methods of quantifying the similarity between two representations. In our discussion of referent free methods we introduced the measure of coherence, which reflects internal consistency of the ratings. It was noted that reliability may also be used as a referent free evaluation. The ideal "good" student is realized when all three measures (C, coherence, and reliability) are high.

## Implications for Curriculum Design and Instruction

The value of assessment is contained in how it is used. If it goes no further than informing a student that she is in the bottom quartile of the class it is of little constructive value. Therefore, it is appropriate to consider some of the important implications of the structural approach for the design of curriculum and methods of instruction.

Because the structural approach that we have proposed involves a comparison between student and expert network representations, it permits the identification of organizational differences at any level of detail. We can go from looking for the presence or absence of specific links between concepts, to looking at more global organizational properties of the two networks. This offers the possibility of providing students with extremely comprehensive feedback, however, it raises the question of how the feedback is to be used. More to the point, what are the instructional implications for differences between student and expert networks?

On the one hand, it is relevant to know that a majority of students in your class do not see the relationship among a certain cluster of concepts on which you have just completed lecturing. Clearly, it is important to have identified this subset of students, but given this information, what do you do about the apparent deficit in their knowledge? It is unlikely that the deficit can be corrected by simply informing the students that concepts A, B, C, and D are all closely related. Presumably they need more information on how these concepts are interrelated, and when that information is provided in an appropriate manner we will see the changes in their network representations. Some support for this is provided in a study by Brown and Stanners (1983). They showed that an MDS representation of a student's organization of concepts in an introductory psychology class could be modified by focused training on a small subset of concepts. The training involved having students make the rating judgments, then publicly defend their rating to the class and the

instructor. In some instances the instructor would then spend several minutes discussing the relationship between specific pairs of concepts.

Another potential advantage of adopting a cognitive structural approach to assessment is that the students can be given an objective goal that has face validity and is theoretically grounded. Moreover, the referent structure itself, represented as a graphic network of interconnected concepts, can serve as a type of organizational schema for readings and lectures. Unlike the conventional outline that forces a linear organization, a network structure can explicitly represent all the important relationships that need to be grasped. With computer software environments such as hypertext it would be possible to implement the empirically derived structure of experts within a domain (Jonassen, 1988). This would allow for intelligent nonlinear browsing through the domain by novices.

General Conclusion and Summary

Our primary motivation in writing the paper was to facilitate communication between traditional test theory and cognitive theory. The central theme addressed the relation between how knowledge is represented and how it is assessed. If our representation of knowledge is organized or structured then our assessment of knowledge must capture this structure and our instruction must reflect the structure. We then outlined how a structural approach to assessment could be implemented and summarized some of the encouraging findings in the area.

In closing, we quickly summarize some of the advantages of the structural approach to assessment. First, a most basic requirement of any assessment technique is that it can be applied to individuals, as can be done with the structural approach. Second, the administration and scoring are completely objective and efficient. Once the concepts or pairs have been selected the entire process can be easily automated on computers. In regard to ease of administration it should also be noted that the program that presents the pairs always randomizes the order of presentation for each subject, thus minimizing order effects and the risk of cheating when administered in groups. Also, it is a simple matter to create multiple versions of the rating task by changing a proportion of the concepts that are paired. This, of course, allows repeated administrations of the task over the duration of a course, which would provide a picture of structural change as learning progresses. Third, although the knowledge that directs our judgments of relatedness is sometimes entirely explicit, it appears, on the basis of students' introspections, that the judgments are often intuitively based and dependent on implicit knowledge. In this regard the approach may nicely complement some conventional exams (e.g., essay) that depend more on explicit knowledge. Fourth, the results not only indicate how much a student knows (e.g., relative similarity to an expert referent structure), but also what specific relationships are misunderstood, and whether the individual is internally consistent (i.e., coherent) in her judgments of relatedness. Fifth, and most important in our opinion, the entire process, involving both training and assessment, is grounded in a common theoretical framework. This should foster greater communication and compatibility between the historically distant areas of psychometric assessment and cognitive theories of representation. Both should benefit from this common orientation.

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